# CEP of On-line Discussions: Multilingual Text Analysis for Early Warning

A Perspective from Sandia's "Networks Grand Challenge"

An Address to the National Academies Standing Committee for Technology Insight—Gauge Evaluate and Review (TIGER)

Philip Kegelmeyer, wpk@sandia.gov, csmr.ca.sandia.gov/~wpk



Sandia is a multiprogram laboratory operated by Sandia Corporation, a Lockheed Martin Company, for the United States Department of Energy's National Nuclear Security Administration under contract DE-AC04-94AL85000.





## CEP: Questions To Address



#### • What is our definition of CEP?

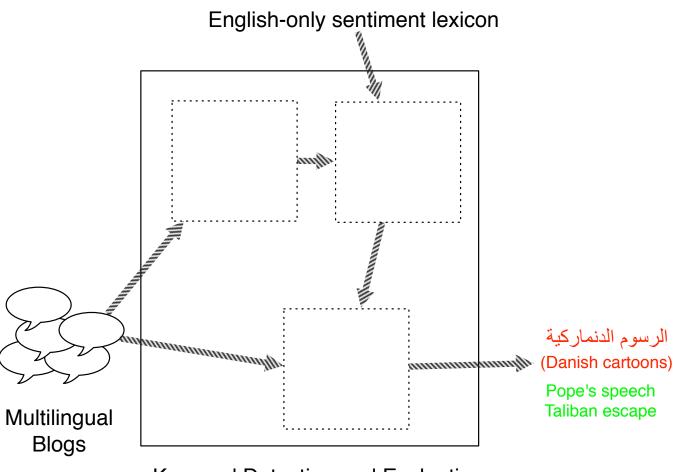
Daily monitoring and analysis of foreign language web blogs to find keywords of IC interest **and** to do predictive analysis as to whether a given keyword discussion will spill over into real world consequences.

- "organization": everyone involved in a on-line discussion domain
- "event": blog post or comment
- "meaningful events": topically coherent blog posts
- "analyzing their impact": forewarning of real world consequences
- How do we do the processing?
- What kind of results do we get?
- Who is using our service and for what?
- What are the computing and data specifications, limitations, metrics?
- What examples of the whole process and success stories?



# The Early Warning Black Box





Keyword Detection and Evaluation



## The Goal of the Networks Grand Challenge



"In this project, we build upon considerable existing Sandia capabilities in scalable computing and advanced analysis algorithms. We will understand and elicit the needs of the intelligence community, do basic research on uncertainty in the intelligence domain, research and evaluate novel analysis algorithms, and implement that research to address those needs to create a flexible, interactive capability for intelligence analysis on large datasets."



## Two Problem Domains of Interest





Cybersecurity<sup>1</sup>

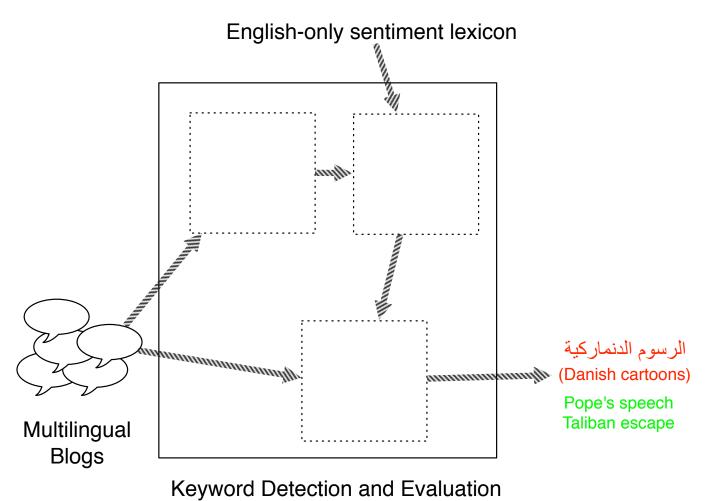


Technology Surprise



# The Early Warning Black Box



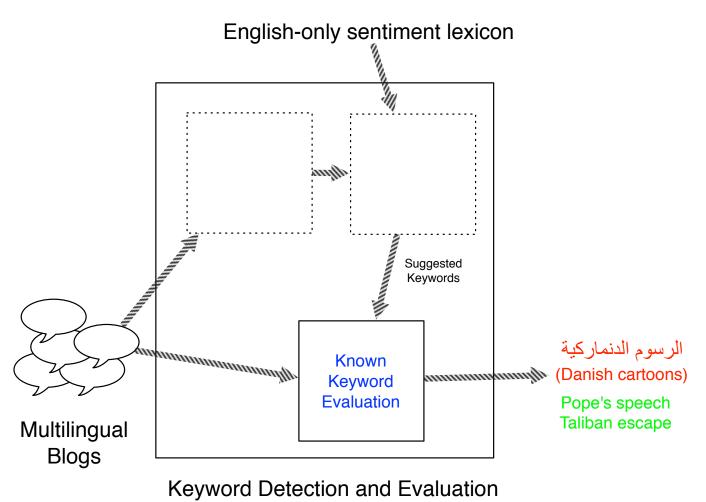


Kegelmeyer, April 27, 2011, NAS/TIGER, "CEP of On-line Text"



## Evaluating Known Keywords

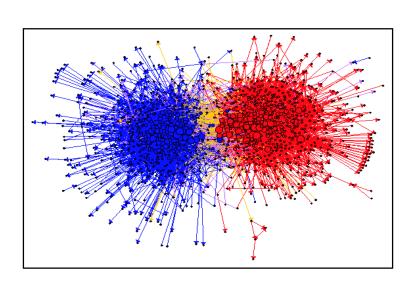


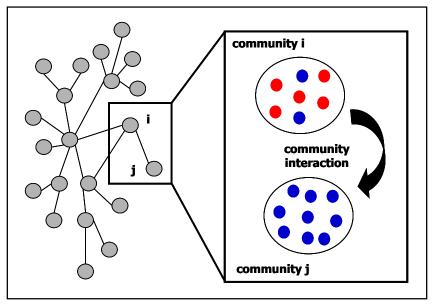


# Multi-scale social dynamics model

A broad range of social dynamics phenomena can be usefully represented within a multi-scale modeling framework:

- micro-scale behavior of individuals;
- meso-scale interactions within social network communities;
- macro-scale interactions between communities.

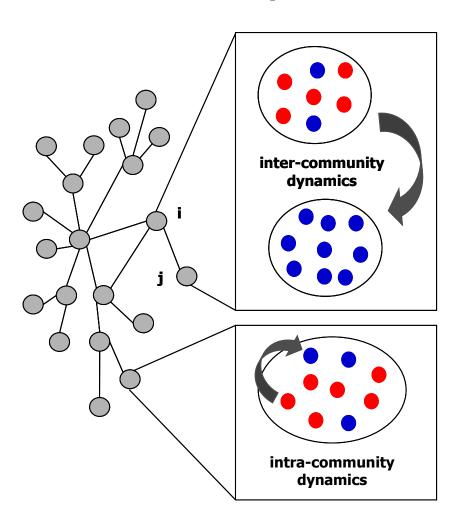




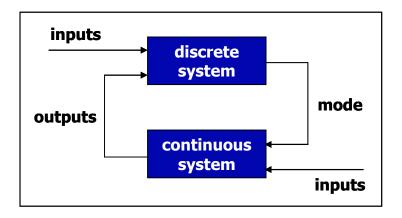


## Stochastic Hybrid Dynamic Systems

## Multi-scale social dynamics model: S-HDS realization



The stochastic hybrid dynamical system (S-HDS) model provides a natural and powerful formalism within which to represent multi-scale social dynamics (expressive, scalable, amenable to formal analysis).

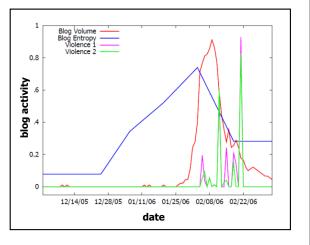


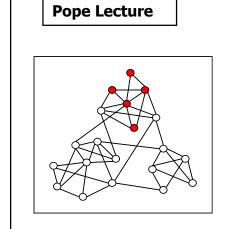


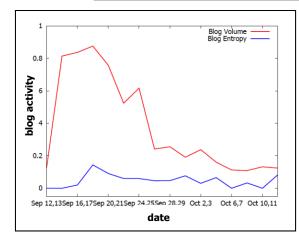
## Entropy as an early indicator ...

Blog post dispersion across communities is an useful early indicator of large mobilizations.

# Danish Cartoons 1







Predictive Analysis

Metric Predictive?

post entropy yes (p<0.002)

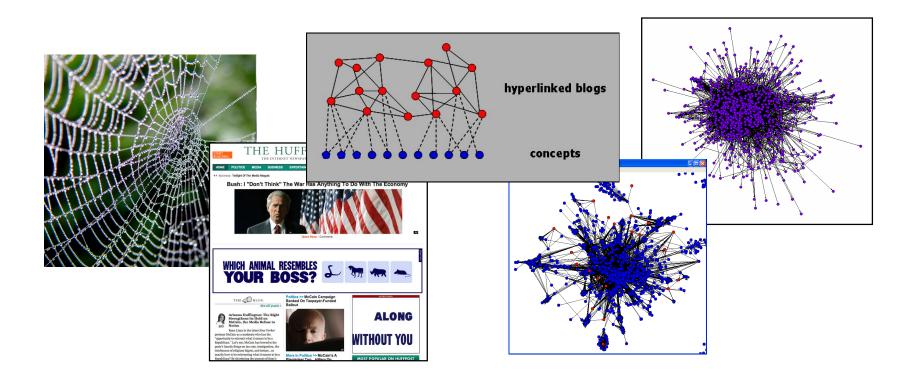
post volume no
lexicon intrinsics no



# 'Known keywords' alert: web crawl

Given set of keywords associated with an emerging (or potential) event of interest, we describe a four step process for generating warning alerts.

Step One: Perform web crawl, construct blog graph, detect keywords and timestamps in posts.

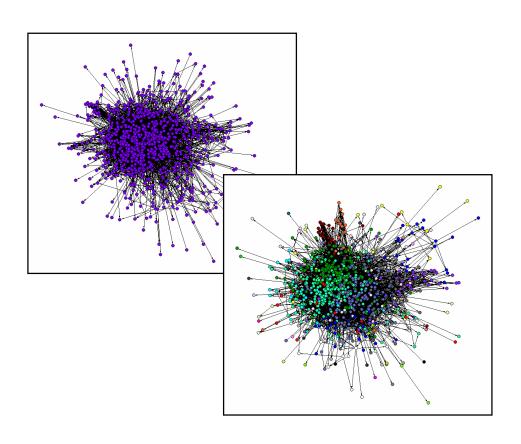


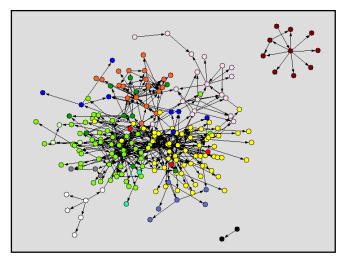


# 'Known keywords' alert: communities

## 'Known keywords' alerting procedure (cont'd)

Step Two: Partition blog graph into social network communities using new weighted CNM (wCNM) algorithm.

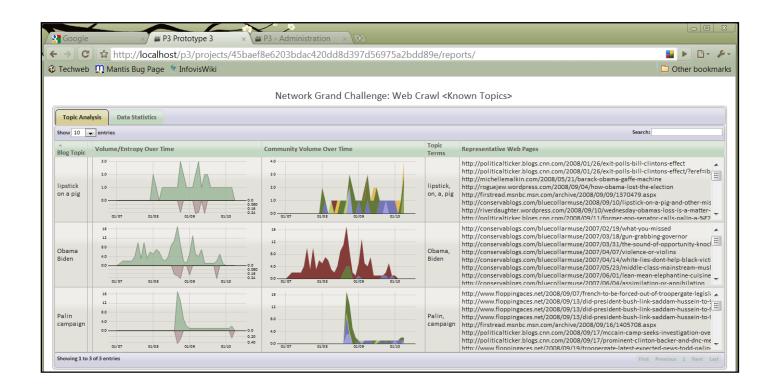




# 'Known keywords' alert: volume, entropy

## 'Known keywords' alerting procedure (cont'd)

Step Three: Assemble time series of post volume and post entropy



# 'Known keywords' alert: compare to 'normal'

## 'Known keywords' alerting procedure (cont'd)

Step Four: Decide if post entropy ent(t) is 'large' and, if so, send alert.

Method 1: multiplier method.

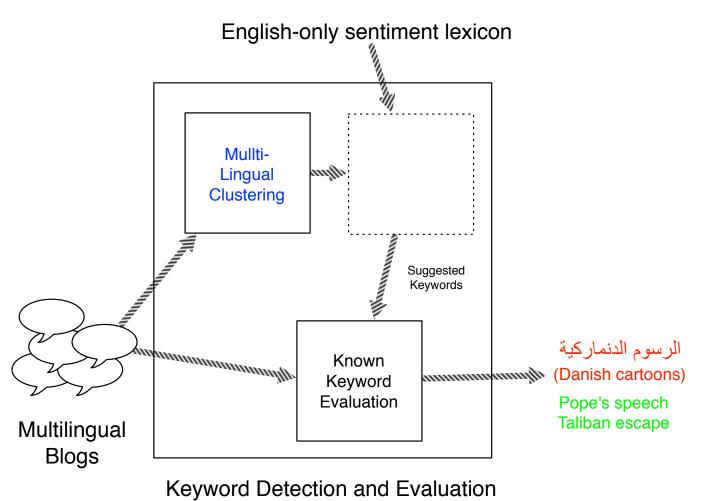
### Offline:

- 1. Construct S-HDS social diffusion model that possesses correct social community graph and produces 'stylized facts' of vol(t) dynamics.
- 2. Generate ensemble of entropy time series  $\{\text{sent}_i(t)\}$  corresponding to null hypothesis: diffusion initiates in one (or a few) communities.
- 3. Determine multiplier  $\lambda$  such that:  $\lambda \times \text{vol}(t) \approx \mu\{\text{sent}_i(t)\} + \sigma\{\text{sent}_i(t)\}$ . Online: Alert if ent(t) >  $\lambda \times \text{vol}(t)$  for any t before 'peak' in vol(t).
- Method 2: direct method.
   Similar but construct {sent<sub>i</sub>(t)} online and compare ent(t) w/ {sent<sub>i</sub>(t)}.



## Multi-lingual Text Clustering





# SNL has developed multilingual text analysis to link threats across multiple languages

 "Translate" new documents into a language-independent concept space, which is useful for:

Translation triage (i.e., translate documents in clusters of interest)

Ideological classification (e.g., hostile to U.S.)

Multilingual sentiment analysis

Sandia's database: 54 languages: >99% coverage of web

Afrikaans	Estonian	Norwegian
Albanian	Finnish	Persian (Farsi)
Amharic	French	Polish
Arabic	German	Portuguese
Aramaic	Greek (New Testament)	Romani
Armenian Eastern	Greek (Modern)	Romanian
Armenian Western	Hebrew (Old Testament)	Russian
Basque	Hebrew (Modern)	Scots Gaelic
Breton	Hungarian	Spanish
Chamorro	Indonesian	Swahili
Chinese (Simplified)	Italian	Swedish
Chinese (Traditional)	Japanese	Tagalog
Croatian	Korean	Thai
Czech	Latin	Turkish
Danish	Latvian	Ukrainian
Dutch	Lithuanian	Vietnamese
English	Manx Gaelic	Wolof
Esperanto	Maori	Xhosa







**English** 

French

Arabic

Spanish

# **Bag of Words/Vector Space Model**

example from (Berry, Drmac, Jessup, 1999)

#### **Documents**

D1: How to <u>Bake Bread Without Recipes</u>

D2: The Classic Art of Viennese Pastry

D3: Numerical Recipes: The Art of Scientific Computing

D4: <u>Breads</u>, <u>Pastries</u>, <u>Pies</u> and <u>Cakes</u>: Quantity Baking Recipes

D5: Pastry: A Book of Best French Recipes

#### **Terms**

T1: bak(e,ing)

T2: recipes

T3: bread

T4: cake

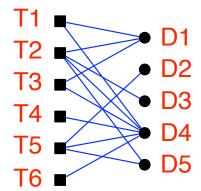
T5: pastr(y,ies)

T6: pie

## Key concepts

- Bag of words
- Stemming
- Vector space model
- Scaling for information content

## Bipartite graph



Term-by-doc (adjacency) matrix

D1 D2 D3 D4 D5

$$\hat{A} = \begin{pmatrix} 1 & 0 & 0 & 1 & 0 \\ 1 & 0 & 1 & 1 & 1 \\ 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 & 0 \end{pmatrix} \begin{array}{c} \mathsf{T1} \\ \mathsf{T2} \\ \mathsf{T3} \\ \mathsf{T4} \\ \mathsf{T5} \\ \mathsf{T6} \\ \end{pmatrix}$$

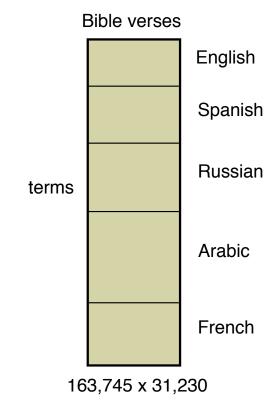




## **Term-Doc Matrix**

# Term-by-verse matrix for all languages





Look for co-occurrence of terms in the same verses and across languages to capture latent concepts

- Approach is not new: pairs of languages in Latent Semantic Analysis (LSA)
  - English and French (Landauer & Littman, 1990)
  - English and Greek (Young, 1994)
- Multi-parallel corpus is new



## **Europarl Corpus**

- Extracted from the proceedings of the European Parliament
- Translations in 11 languages
  - French, Italian, Spanish, Portuguese (Romantic)
  - English, Dutch, German, Danish, Swedish (Germanic)
  - Greek
  - Finnish
- Sentence aligned text (16 M sentences across 11 languages)
- 1,247,832 speeches (including translations)
- 1,249,253 terms (from all 11 languages)
  - English terms: 46,074



# Multilingual Latent Semantic Analysis

for all languages reduced representation docs English Spanish Truncated **Project SVD** new documents Russian X U terms **Arabic** French term x concept

"Translate" new documents into a small number of language-independent features

dimension 1	0.1375
dimension 2	0.1052
dimension 3	0.0341
dimension 4	0.0441
dimension 5	-0.0087
dimension 6	0.0410
dimension 7	0.1011
dimension 8	0.0020
dimension 9	0.0518
dimension 10	0.0822
dimension 11	-0.0101
dimension 12	-0.1154
dimension 13	-0.0990
dimension 14	0.0228
dimension 15	-0.0520
dimension 16	0.1096
dimension 17	0.0294
dimension 18	0.0495
dimension 19	0.0553
dimension 20	0.1598

Document feature vector



Term-by-doc matrix

- cross-language retrieval
- · pairwise similarities for clustering
- machine learning applications











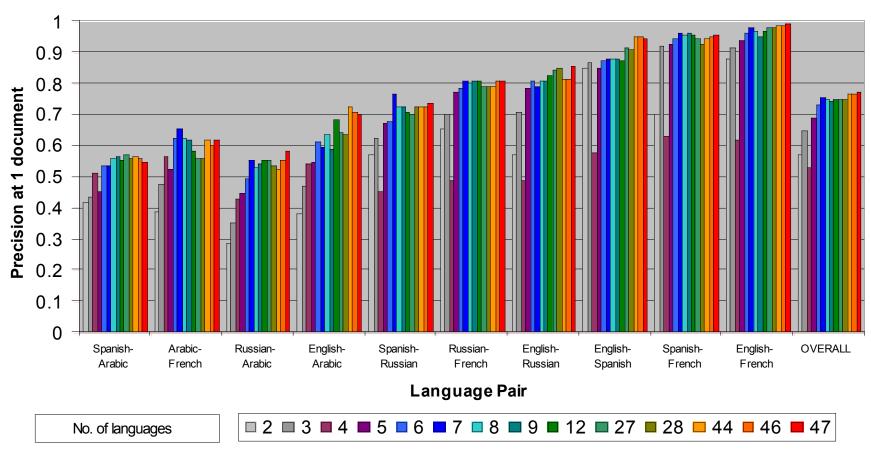




## **More languages = Better results**

(Chew and Abdelali, 2007)

## LSA with 300 concept vectors







## **Language Morphology**

<u>Translation</u>	<u>Terms</u>	<u>Total Words</u>
English (King James)	12,335	789,744
Arabic (Smith Van Dyke)	55,300	440,435

Languages convey information in different number of words

Isolating language

Synthetic language

Chinese

Quechua, Inuit (Eskimo)

- Isolating language: One morpheme per word
  - e.g., "He travelled by hovercraft on the sea." Largely isolating, but travelled and hovercraft each have two morphemes per word. (Wikipedia)
- Synthetic language: High morpheme-per-word ratio
  - German: Aufsichtsratsmitgliederversammlung => "On-view-council-with-limbs-gathering" meaning "meeting of members of the supervisory board". (Wikipedia)
  - Chulym: Aalychtypiskem => "I went out moose hunting"
  - Yup'ik Eskimo: tuntussuqatarniksaitengqiggtuq => "He had not yet said again that he was going to hunt reindeer." (Payne, 1997)





# **Sample Tokenization**

Wordform	<u>Tokenization</u>
abaissée	abaissé + e
abaissées	abaissé + es
abaissèrent	abaiss + èrent
acceptance	accept + ance
acceptation	accept + ation
acquaintance	acquaint + ance

We use these "morphemes" in place of terms

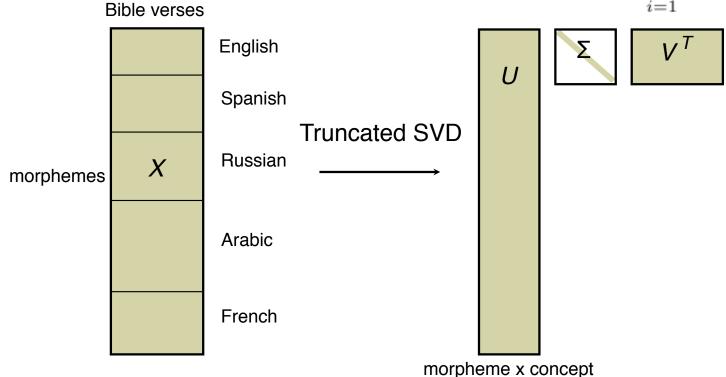




# Latent Morpho-Semantic Analysis (LMSA)

# Morpheme-by-verse matrix for all languages

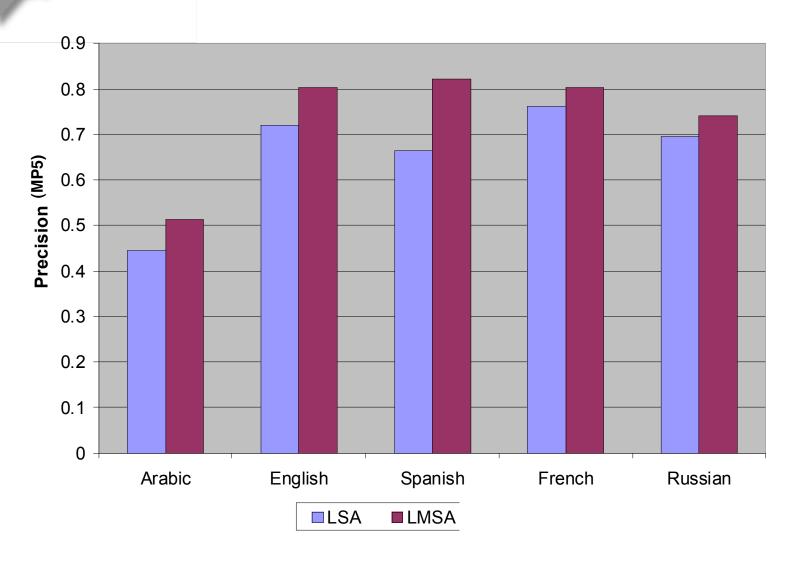
$$X_{\mathbf{k}} = U_{\mathbf{k}} \Sigma_{\mathbf{k}} V_{\mathbf{k}}^{T} = \sum_{i=1}^{\mathbf{k}} \sigma_{i} u_{i} v_{i}^{T}$$



- Fewer morphemes than terms
- X matrix is smaller but denser







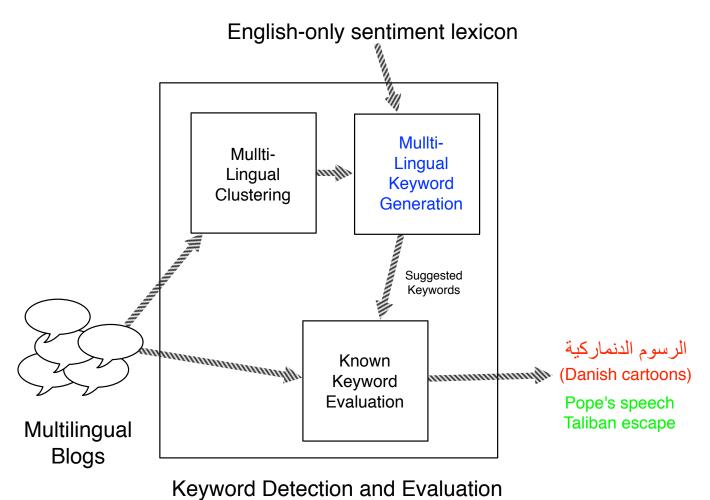
Statistically significant improvements at p < 0.001





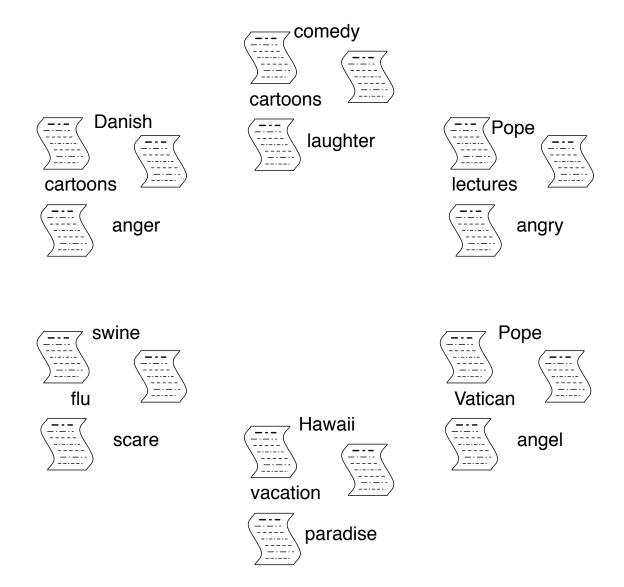
# Multi-lingual Sentiment Analysis





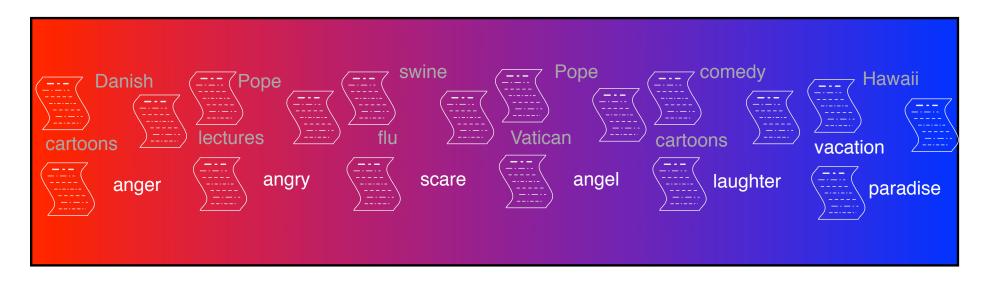
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1) Sort the documents according to sentiment

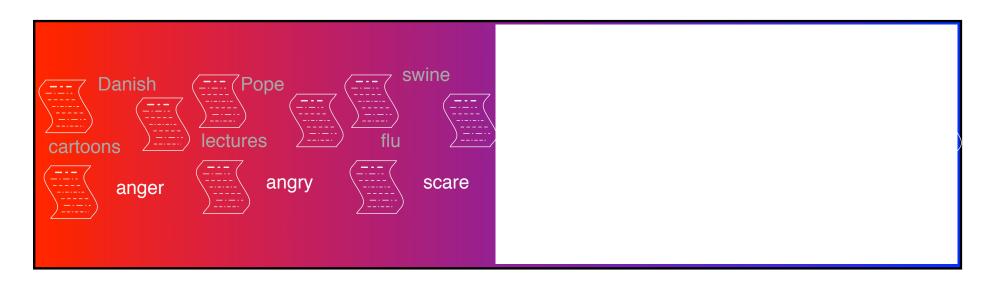


Unpleasant





2) Keep only the highly emotional documents

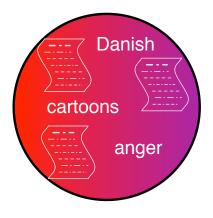


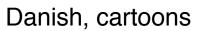
Unpleasant Ambivalent Pleasant

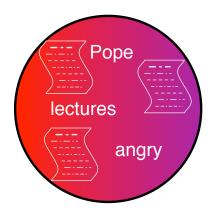




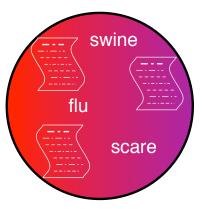
- 3) Cluster by topic using multilingual document clustering
- 4) Find unique keywords that describe each cluster







Pope, lectures



swine, flu



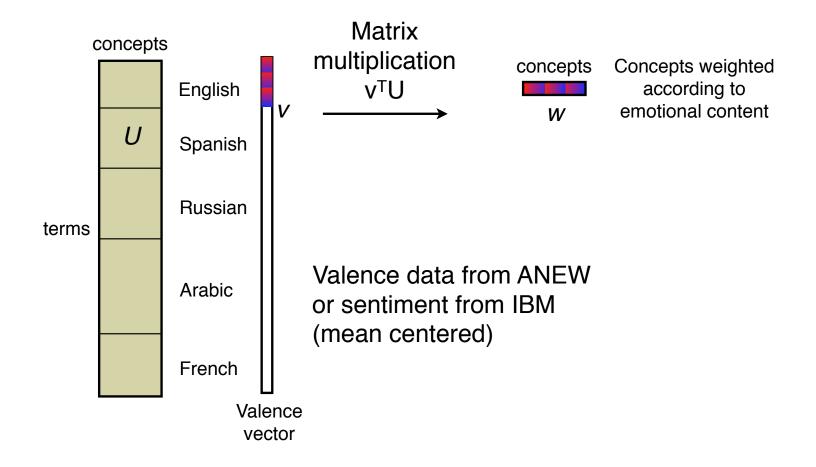
## **Extracting Sentiment from Text**

- In English, there are a number of sentiment lexicons and emotional valence dictionaries
  - IBM
  - Affective Norms for English Words (ANEW)
  - Harvard IV-4
  - Lasswell value dictionary
  - Whissell's Dictionary of Affect in Language (DAL)
  - **-** ...
- We would like to avoid a dependence on sentiment lexicons for foreign languages
  - Otherwise complexity increases!
  - Need to keep up with evolving/changing language
  - IC interest in least-spoken languages whereas commercial systems target most-spoken languages
  - "Early warning sentiment analysis"

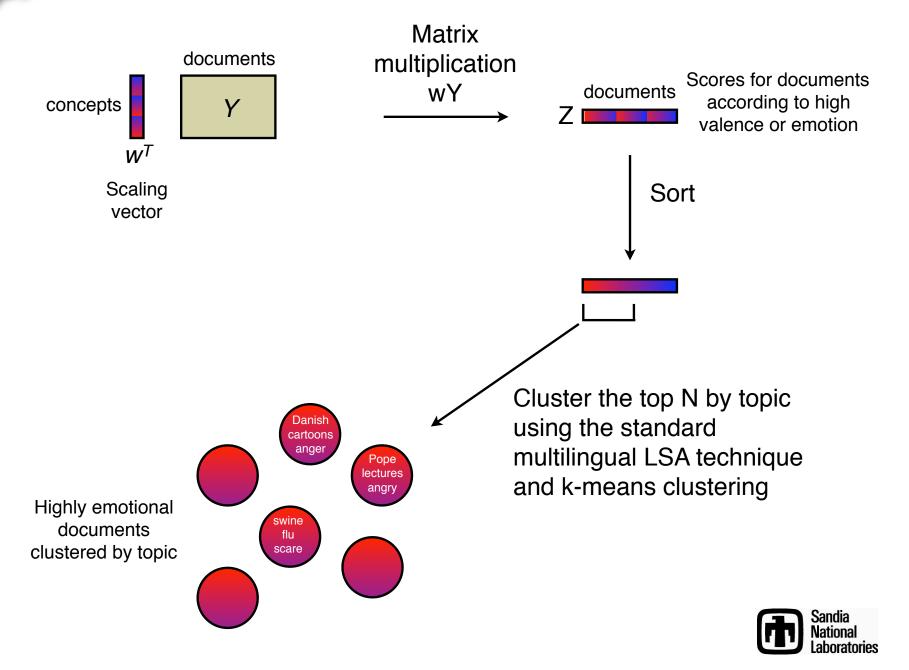


## **Concept Weighting and Scaling**

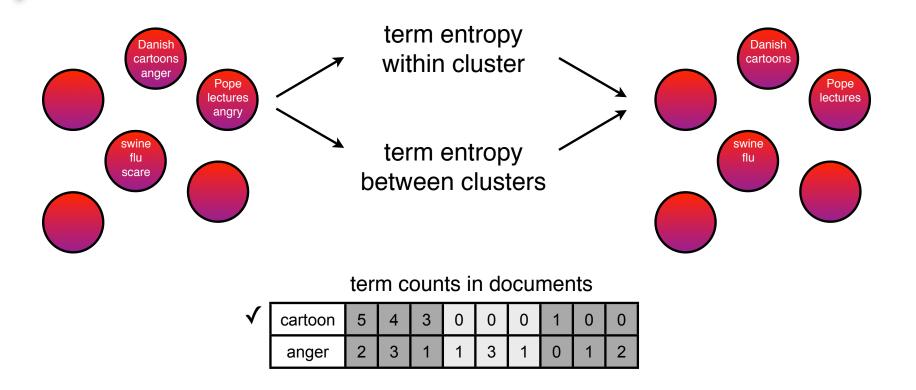
Identify concepts associated with words with high valence



## Ranking, Sorting, Clustering



## **Identify Keywords**



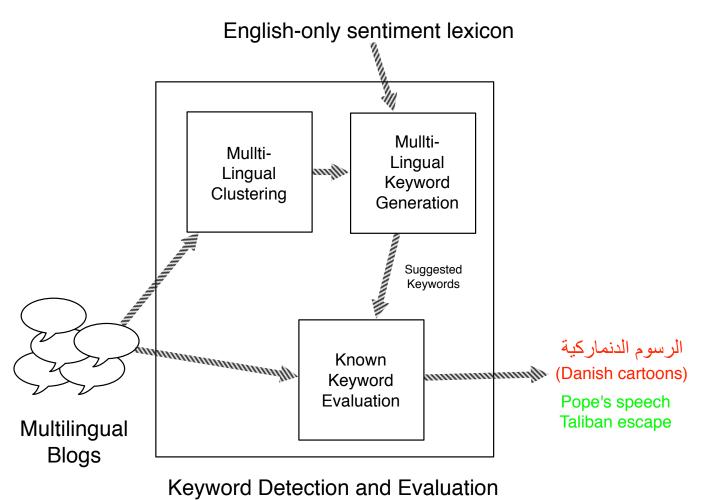
- Find unique terms that best describe each cluster.
- The idea is that we want to identify terms that have broad coverage within a cluster but don't appear much outside of this cluster.
- Choose terms with low inter-cluster entropy but high intra-cluster entropy (e.g., by dividing the intra- by inter-entropy scores and choosing the top N terms per cluster on this scale).





## The Black Box, Unpacked ...





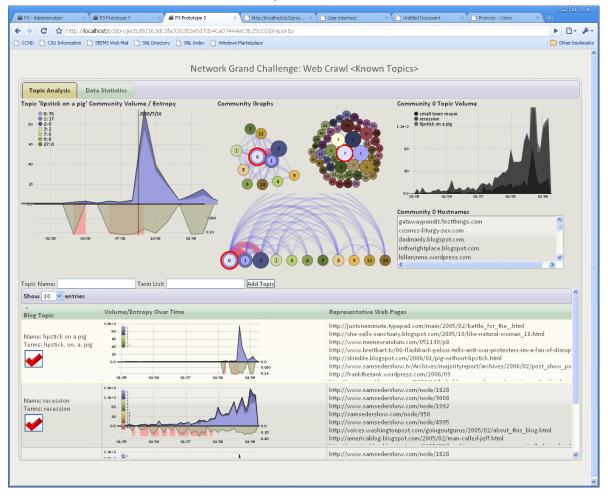
Kegelmeyer, April 27, 2011, NAS/TIGER, "CEP of On-line Text"



## All Implemented in an Analyst's Tool



## Interactive web interface, built in Titan and ProtoVis





## CEP: Questions To Address (Part 1)



- What is our definition of CEP?
- How do we do the processing?

Nightly web crawls, multi-lingual clustering, keyword generation and evaluation.

- What kind of results do we get?
  - Red/Green binary keyword alerts.
  - Volume and entropy time series plots for all keywords.
  - Drill down to source blogs at any point.



## CEP: Questions To Address (Part 2)



### Who is using our service and for what?

Sandia analysts, for cultural reaction assessments.

Capabilities shared with DoD, IC, JASONS.

- What are the computing and data specifications, limitations, metrics?
  - Primary limitations: pairwise similarity calculations, ugliness of web data.
  - Metrics: customer anecdotes. Clustering validation, keyword replication, and sentiment prediction studies. Peer-reviewed publication.
- What examples of the whole process and success stories?

Bali-bomber execution in early November 2008; correctly predicted that outrage was **not** self-sustaining.

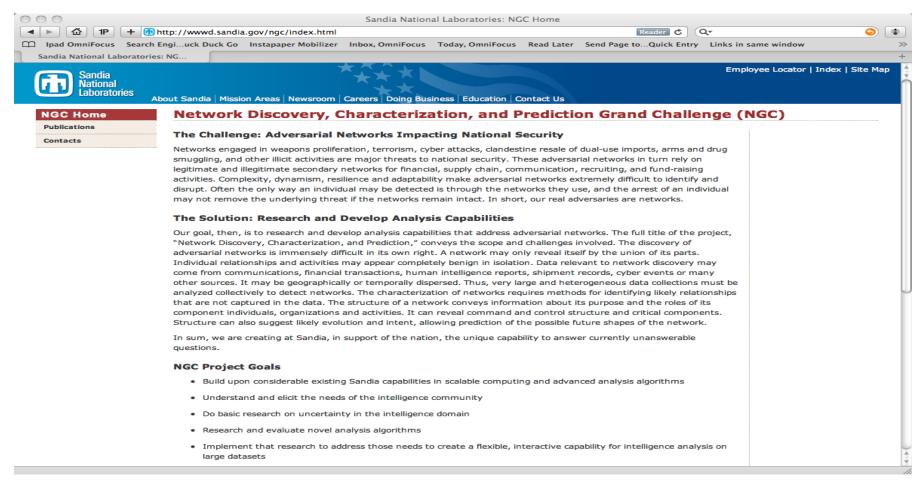
Israel/Gaza conflict in early January 2009; correctly predicted that hacking discussion was self-sustaining, then actual hacking occurs.



## For More Information ...



• NGC Final Report, all publications, all contact info: ngc.sandia.gov



- Predictions from communities: Rich Colbaugh, rcolbau@sandia.gov, 505 284-4116
- Multilingual text analysis: Brett Bader, bwbader@sandia.gov, 505 845-0514
- PI, and sentiment analysis: Philip Kegelmeyer, wpk@sandia.gov, 925 294-3016